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A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts ☆

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HIGHLIGHTS

- Working with unique datasets of EV charging and smart meter load demand.
- Distribution networks are not a homogenous group with more capabilities to accommodate EVs than previously suggested.
- Spatial and temporal diversity of EV charging demand alleviate the impacts on networks.
- An extensive recharging infrastructure could enable connection of additional EVs on constrained distribution networks.
- Electric utilities could increase the network capability to accommodate EVs by investing in recharging infrastructure.

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ABSTRACT

This work uses a probabilistic method to combine two unique datasets of real world electric vehicle charging profiles and residential smart meter load demand. The data was used to study the impact of the uptake of Electric Vehicles (EVs) on electricity distribution networks. Two real networks representing an urban and rural area, and a generic network representative of a heavily loaded UK distribution network were used. The findings show that distribution networks are not a homogeneous group with a variation of capabilities to accommodate EVs and there is a greater capability than previous studies have suggested. Consideration of the spatial and temporal diversity of EV charging demand has been demonstrated to reduce the estimated impacts on the distribution networks. It is suggested that distribution network operators could collaborate with new market players, such as charging infrastructure operators, to support the roll out of an extensive charging infrastructure in a way that makes the network more robust; create more opportunities for demand side management; and reduce planning uncertainties associated with the stochastic nature of EV charging demand.

1. Introduction

The UK government passed the Climate Change Act which established a legally binding target of cutting the UK's greenhouse gas emissions by at least 80% compared to 1990 levels by 2050 [1]. In order to make the transition to a low carbon economy, the government published the Carbon Plan in 2011 which sets outs a strategy to achieve the decarbonisation target across sectors. A quarter of the UK emissions come from the domestic transport sector which needs to substantially reduce its emissions by 2050. The Carbon Plan emphasizes the need for a move towards a mass market roll-out of ultra-low emission vehicles such as Electric Vehicles (EVs) to achieve the deep cuts required [2]. It would then be important to investigate the potential impact of a significant take up of EVs on the electricity system in the UK; in particular, this work will focus on the impact on electricity distribution networks of residential uncontrolled and clustered charging of EVs.

Several studies have already looked at the impacts of the uncoordinated charging of EVs on distribution networks. The potential impacts on Low Voltage (LV) distribution networks include voltage variations, transformer and thermal limit violations. However, these studies based their work on estimated rather than actual EV charging behaviour and smart meter data. Most of the charging data used in these previous studies was derived from driving patterns collected in national transportation surveys in order to

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estimate certain aspects of EV usage; such as journey distance and energy used, parking location and time, State-of-Charge (SoC) at the beginning of a charging event and the plug-in time. Some of these studies assumed that the charging starts immediately upon the users' home arrival while others assumed that a large proportion of charging starts from a low SoC. Furthermore, some of the studies considered that users would only charge at home and did not consider the availability of a public charging infrastructure [3–17].

Using the derived charging profiles, the studies demonstrated that the impacts of uncontrolled EV charging in residential areas were detrimental to the operation of distribution networks. Some studies demonstrated thermal limit violations and voltage drops below acceptable limits for EV penetration of 50% [11–13]. One study stated that with 50% EV penetration, there would be significant impacts on the operating conditions of the distribution networks and uncontrolled charging could require major infrastructure upgrades [14]. Another study [15] showed that a 25% penetration of EVs in residential areas would cause considerable voltage dropping below the statutory limit while [16] stated that the distribution network can handle only up to 10% EV penetration without changes in the usual electricity grid operation and planning procedures. One of the studies that focused on British distribution networks found that a 12.5% uptake would cause severe impacts on the transformer and the LV underground cable supplying the households [17]. In this study a probabilistic approach was used to address uncertainties associated with residential loads and EV user behaviour such as plug-in time and SoC. The authors noted that real-world data of EV usage comprising more accurate charge durations, connection times and a reflection on the use of the additional recharging infrastructure (i.e. work, public) could be the focus of further work on the subject and could help improve the probabilistic methods used.

The significance of the present work is that it is based on a unique combination of two comprehensive high resolution spatio-temporal real-world data sets of EV driving and charging patterns and residential smart meter data. The use of real-world data avoids the need to make assumptions about the stochastic nature of vehicle use and would minimise uncertainties associated with simulated charging demand. Based on real-world datasets, this paper demonstrates that distribution networks could accommodate higher EV penetrations than previous studies have suggested.

The EV data is collected from the SwitchEV project which trialled 44 EVs in the North East of England between 2010 and 2013. The cars were fitted with data loggers that captured more than 85,000 EV journeys recorded second by second and over 19,000 recharging events recorded minute by minute at more than 650 public and 260 private charging points [18,19]. The smart meter data was collected via the Customer Led Network Revolution (CLNR) project. This is the UK's largest trial of smart grids and it provided domestic load profiles of half-hourly power consumption data collected from nearly 9000 smart meters. In addition, the CLNR smart meter data set [20] is parameterised by socio-economic variables which allow the selection of representative load profiles appropriate to the network customer population under study. The four-year CLNR project also provided network data and extensively validated network models based on existing local distribution networks operated by the regional distribution network operator (DNO), Northern Powergrid.

This work is an elaboration on [21], extended to include the impacts on a generic distribution network to provide broad value and replicability for the whole of the UK. This is in addition to the urban and rural case study networks. A more comprehensive distribution network impact analysis has been undertaken using IPSA2 (steady-state, balanced three phase network) and PSCAD (Electromagnetic transient analysis for voltage unbalance analysis); and a more extensive results and discussion sections. Section 2 describes the EVs' data, the smart meter data and network models used for this study (including network validation). Section 3 describes our modelling framework to study the impact on the distribution network. The results of the study are presented in Section 4; the discussion and conclusions of this work are presented in Section 5.

2. Data

2.1. Electric vehicles trial – SwitchEV project

High resolution spatial and temporal data of EV driving and charging events were collected, processed and analysed during the SwitchEV project. The dataset gave insight and illustrated the stochastic nature of real world behaviour of EV users. The project recruited different types of users- private and fleet drivers. They had access to an extensive charging infrastructure (home, work, public). The majority of vehicles used in the trial are production vehicles available on the market and were provided by Nissan (LEAF) and Peugeot (iOn). A total of 125 different users were recruited for the duration of the project [19]. As a result, the data collected from the SwitchEV trial captured how people would use an electric car in a real-world context.

2.1.1. The electric vehicle is the primary vehicle

Participants on the trial leased the cars for 6 months which allowed them to get familiar with the vehicle. Shortly after the beginning of their 6-month trial, the participants reported that they had trusted the EV to be their primary car. To verify that the EVs were used in an equivalent fashion to primary vehicles, the authors compared the daily mileage of the Switch EV vehicles collected from the data loggers (Fig. 1) and the National Travel Survey (NTS) mileage data in Great Britain (GB) for conventional cars. The Department for Transport NTS data provides information on personal travel on all mode of transport in GB [22]. Daily average distance travelled was not available; however, according to the NTS the average distance travelled per person per year by car/van drivers is 5207 km. It was assumed that drivers could be using their cars 5 times a week and as such it was estimated that the average distance travelled per person per day by car drivers is 20 km. The average daily mileage of the EV drivers on the trial is 38.9 km, almost the double of the national average, suggesting that the electric vehicles on trial were used as the primary vehicle, as reported by the drivers. Fig. 2 shows the responses collected from the post-trial questionnaires regarding the reasons for driving the electric vehicle.

2.1.2. Real and diverse EV usage profiles (charging and driving)

This work focuses on the charging profile of users. The variables recorded during the recharging events include the time, battery current and voltage along with its State of Charge (SoC). These variables are then used to determine secondary variables such as the duration of a charge event and the energy transferred. However, the driving profile (driving behaviour and driving conditions) is also important because it would determine the SoC of the EV battery before it is plugged in for recharging. The driving profile is briefly described in the two following paragraphs.

The SwitchEV trial recorded trips of varying length ranging from less than 1 km to over 100 km; it also recorded the number of trips between two consecutive charging events. Previous work using the SwitchEV data has demonstrated that driving behaviour of users (i.e. speed) and driving conditions such as the topography of the road network and the network conditions (i.e. free flow, congested)

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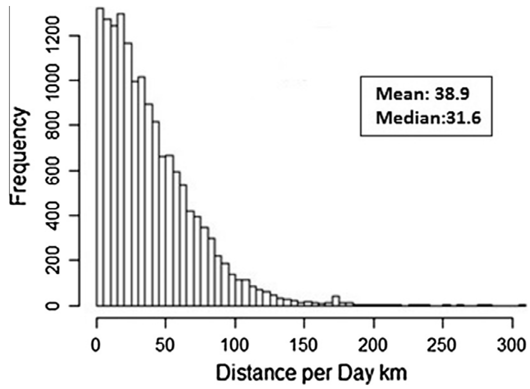

Fig. 1. Distribution of daily mileage of the EV users on the SwitchEV trial.

affects the driving energy efficiency of the vehicle and the residual energy at the end of a driving event [23]. The trial took place over different seasons which enabled the capture of the effects of outside temperature. Temperature affects driving efficiency as lower temperatures would typically lead to the use of the in-car heater fed from the traction battery of the car. This increases the energy used while driving and subsequently further lowers the SoC.

As an example, Fig. 3 illustrates the impact of driving behaviour on energy used for journeys. Different drivers are taking an identical spatial journey as part of an EV trial and their different driving styles result in a different battery drain. At a lower SoC, resulting from an aggressive drive for example, the battery would take more time and energy to return to a level of charge that makes the driver comfortable in using the vehicle again.

The SoC levels recorded during the trial capture the stochastic nature and behavioural diversity of the users. The boxplots in Fig. 4 show the SoC levels of the battery at the beginning of a charging event (left boxplot) and at the end of a charging event (right boxplot). The SoC observations corresponds to the residential charging events recorded during the trial (3332 events). For example, it can be observed that 50% of the charging events started at an SoC $\geqslant$ 53%. These diverse SoC levels would result in a diverse range of charging profiles that were used in this study – moving away from using a fixed energy, static spatio-temporal charging period.

2.1.3. Real and varied charging infrastructure

The SwitchEV trial is distinctive because it collaborated with Charge Your Car (North Ltd) (CYC), the operator of the North East of England's "Plugged in Places" project, which has provided one of the most extensive regional charging networks in Europe with

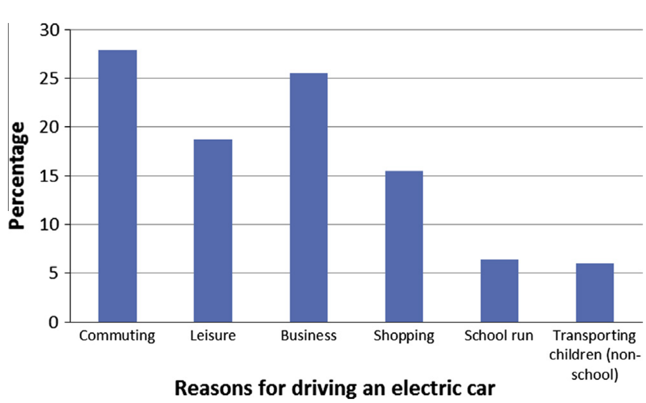

Fig. 2. SwitchEV post-trial questionnaires responses on reasons for driving an EV.

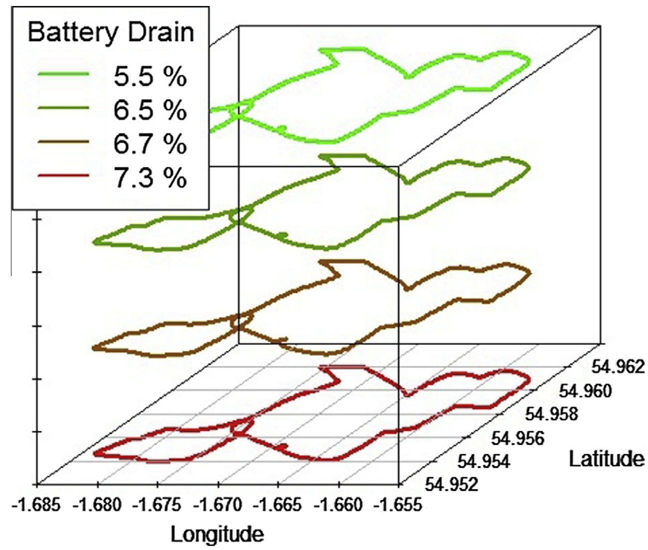

Fig. 3. Illustration of different driving behaviour of four users driving the same route as part of an EV trial. Bottom red journey (7.3% battery drain); top green journey (5.5% battery drain). The colour change denotes the change in driving energy efficiency. The journeys are evenly spaced on the Z-axis to obtain a clearer graph. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

more than 900 charging posts installed in public, work and home locations in the region during the SwitchEV trial. As a consequence, the participants were not limited to one charging location and they had real and varied options about when and where to charge. Their homes and work places could be equipped with charging units; they could access charging posts on-street and in commercial places and public car parks; and there were twelve accessible 50 kW DC Rapid Chargers (RC) installed at strategic locations in the region. The RCs allow a car to recharge from an empty battery (SoC = 0%) to 80% in less than 30 min. The analysis of the dataset collected identified the charging locations used and the energy transferred at each of these locations. This analysis allowed the extraction of home charging events that were used for this study. This extensive and flexible infrastructure was reflected in the charging profiles and was key to the results obtained in this study that will be described in Section 5.

2.1.4. Keepership type and residence setting

The EVs on the trial were leased as private and fleet cars. The charging profiles of private cars were used in this study.

To determine the residence setting (i.e. urban vs rural) of the users on the SwitchEV trial, the Office for National Statistics Postcode Directory (ONSPD) was used. Postcodes on the ONSPD are assigned to urban or rural categories [24]. The postcode of the SwitchEV users were identified in the ONSPD and their residence setting was then determined. It was found that 70% of the SwitchEV users reside in urban areas while 30% reside in rural areas.

Fig. 5 presents an overview of all charging events for the private users at all locations. It shows the percentage of the average energy transferred at different locations per hour of the day for private urban (top figure) and private rural users (lower figure). It can be observed that charging events were recorded at different locations (home, work, public, RC). Urban users in particular used the public infrastructure significantly. Most of the work charging events happened during the day as would be expected. Home charging picks up in the afternoon and a noticeable additional charging peak occurs at midnight for both urban and rural participants. The midnight

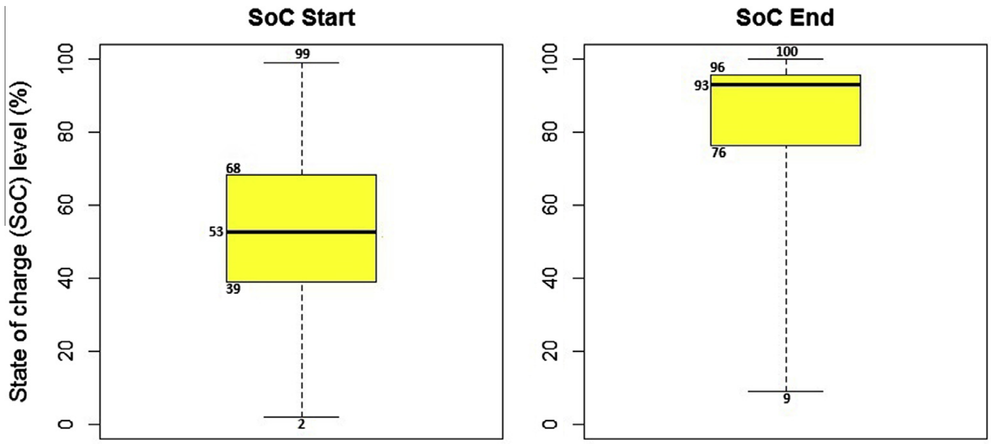

Fig. 4. Boxplots of State of Charge (SoC) of the batteries of the cars on trial. Before charging (left) and after charging (right). The vertical dimension of the boxes display the variation of the data. The bottom of the box is the 25th percentile of the data (SoC value below which 25% of the observations may be found). The top of the box is the 75th percentile of the data. The horizontal bold line inside the box is the median (50th percentile of the data). The end of the whiskers (lines extending vertically from the boxes) can represent several alternative values; for this graph, we chose them to represent the minimum and maximum of all of the observations.

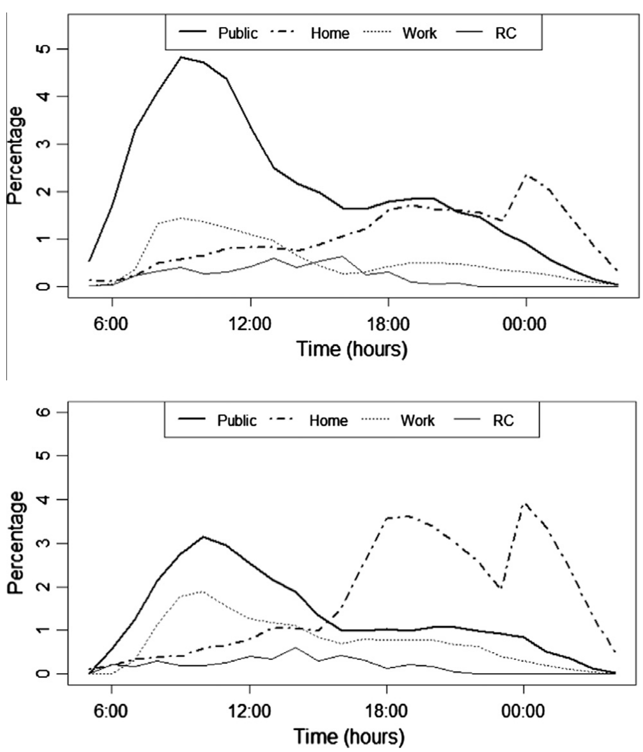

Fig. 5. Percentage energy transferred at each hour of the day for all charging events at different charging locations. Urban users (top figure) and rural users (lower figure).

peak could be explained by some home chargers equipped with a timer set to start charging at midnight. Finally, rural users rely more on home charging compared to urban users.

2.2. Smart grid trial – Customer Led Network Revolution (CLNR) project

2.2.1. Smart meter data

In order to understand present and emerging load and distributed generation patterns, the CLNR project is conducting monitoring trials using data from over 9000 smart meters placed in residential locations in the UK. The smart meter dataset is

Table 1
Summary of LV network and population parameters.

	"Urban"	"Rural"
Substation	6.6 kV/400 V 500 kVA	20 kV/400 V 315 kVA
Feeders	4	2
Total LV customers	288	189
Number of customers per LV feeder	A-59, B-66, C-84, D-79	A-123, B-66
Vehicle ownership	86%	74.6%
No. of vehicles in vehicle-owning households	1.7	1.5
ONS morphology code	1 (Urban)	3 (Rural)
House thermal efficiency	Medium	Medium
Percentage households with under 5 s or over 65 s	44%	40%
Equivalent annual income (gross)	60%: >£30 k 35%: £15–£30 k 5%: <£15 k	18%: >£30 k 62%: £15–£30 k 20%: <£15 k
Tenure	Effective 100% home ownership	37% Renting 63% Owned
Household occupancy	97%	97%

classified by household income, presence of under 5 s or over 65 s, tenure, household thermal efficiency and area classification (urban/rural). UK ONS data was used to determine the characteristics of the study areas of this work, which are summarised in Table 1 along with the electricity network characteristics. Using the parameters in Table 1, a representative population of residential load profiles was extracted from the CLNR dataset representing the study areas. Properties in the two regions are mostly mid-20th century semi-detached houses with adjoining off-street parking. Some communal parking facilities are also evident. Vehicle ownership is high and many households own more than one car. Given these observations, these populations are used as model populations of potential future EV owners on their respective networks.

2.2.2. Network models

Previous work suggests that densely-populated urban and sparsely-populated rural LV networks are both likely to be vulnerable to the mass uptake of EVs [7]. As these two network types are estimated to represent approximately 80% of UK networks [3], it is of critical importance to further study these

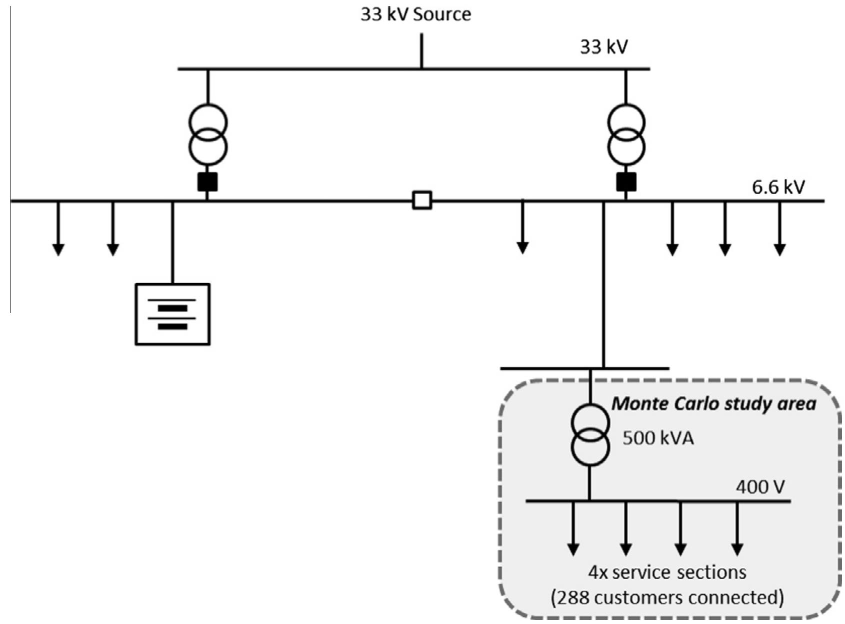

Fig. 6. Diagram of the 6.6 kV case-study urban network used in steady-state IPSA2 study.

scenarios. The CLNR project is using two real networks within Northern Powergrid's licence area – one rural and one urban – to enable evaluation of questions of load growth and active network management. Models of the trial networks have been developed in IPSA2, a steady-state power system simulation application, and these have been extensively validated with two years of detailed network data and against existing DNO network models (using data provided by Northern Powergrid). This study uses this set of models and data as a foundation for the examination of EV load impacts.

The urban network under study (Fig. 6) is a 6.6 kV network supplying approximately 6000 customers, with a mixed load curve and an early-evening peak. One particular HV/LV substation supplying 288 customers via a 500 kVA transformer and 4 LV feeders is studied in detail as a test case for EV penetration.

Fig. 7 shows the rural network under investigation. This consists of a 20 kV feeder, approximately 40 km long, supplying a number of towns in Northumberland in northern England. Three HV/LV substations supply one of these towns; and this paper focuses on one of these substations which supplies 189 residential properties through two multiply-branched LV feeders.

The LV network sections under study are exclusively residential with no industrial or commercial facilities or public EV charging infrastructure supplied by the HV/LV transformer.

In addition, a third 'generic' network (Fig. 8) based on [25], has been studied. This network has been deemed to be a representative of a heavily loaded UK distribution network by UK DNOs who were involved in specifying and creating it. It consists of a 33 kV source feeding two 15 MVA 33/11 kV transformers. There are six 11 kV feeders, each of which have eight 500 kVA 11/0.4 kV transformers equally spaced along 3 km of underground cable. Downstream of each 500 kVA transformer are 4 LV feeders of 300 m in length with 96 customers spaced equally along each feeder. The population parameters for the 386 customers under study on the generic network were assumed to be the same as the urban network described previously in Table 1.

The rural and urban networks give an indication as to the problems that could be encountered in different types of networks. However, all networks are different and therefore the modelling of a specific system is required to establish if localised problems exist. The generic network has been used in this study in order to draw broad and generalizable conclusions across the UK distribution networks as a whole.

2.2.3. Urban and rural network load modelling validation

Representative power consumption data collected from LV monitoring systems installed on the study networks for two winter (January) peak demand mid-week days for both the urban and rural networks were compared in Fig. 9 with randomised customer group demands (sampled from the smart meter dataset for the peak day). This was done to confirm that the modelled networks and simulated customer groupings approximated the real network loading.

It can be seen that the general customer behaviour adequately represents the real load on the respective networks, particularly total peak loading, and the network and customer models are therefore used as a baseline to evaluate the additional EV loading. It has been found[1] that 50% of secondary distribution transformers operate at approximately 50–60% of their nameplate capacity, therefore the HV/LV transformers under study are not atypical.

3. Methods

3.1. Monte Carlo simulations

Peak consumption of electricity is in winter in the UK. In order to assess the additional impact of EVs during an existing peak loading event, a single peak load test day corresponding to the DNO's system peak load day in January is studied.

Monte Carlo Simulation (MCS) was used to build up a distribution of possible demands on the trial networks. Data for the simulation was produced by sampling the domestic load profile and EV charging profile populations. Households on the LV networks were randomly assigned load profiles in proportion to the local demographic makeup. A defined percentage of these users, corresponding to a level of EV penetration, were further assigned an EV load profile which was added to their base domestic profile.

[1] Information provided by Northern Powergrid.

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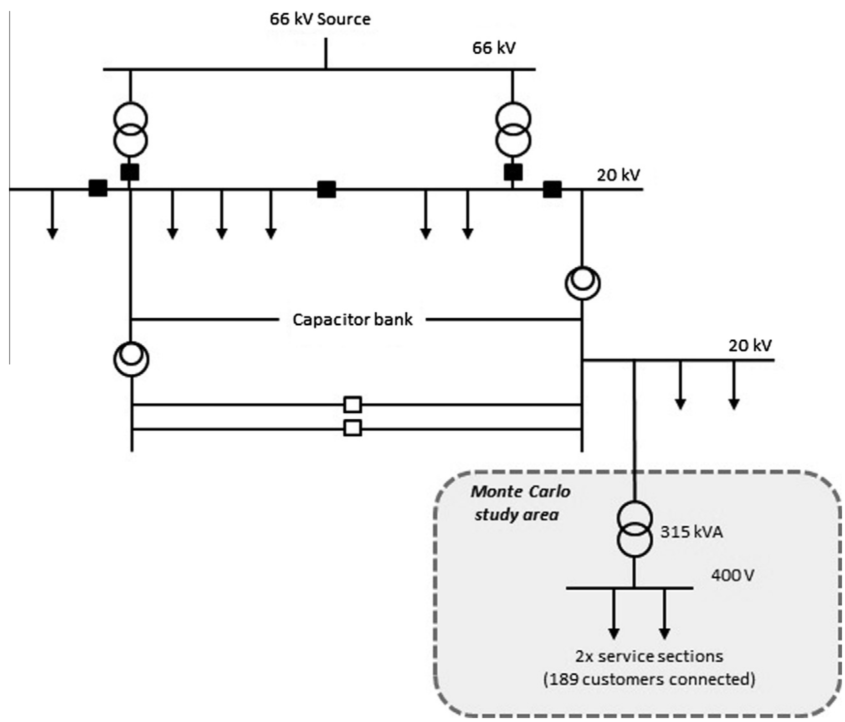

Fig. 7. Diagram of the 20 kV case-study rural network used in steady-state IPSA2 study.

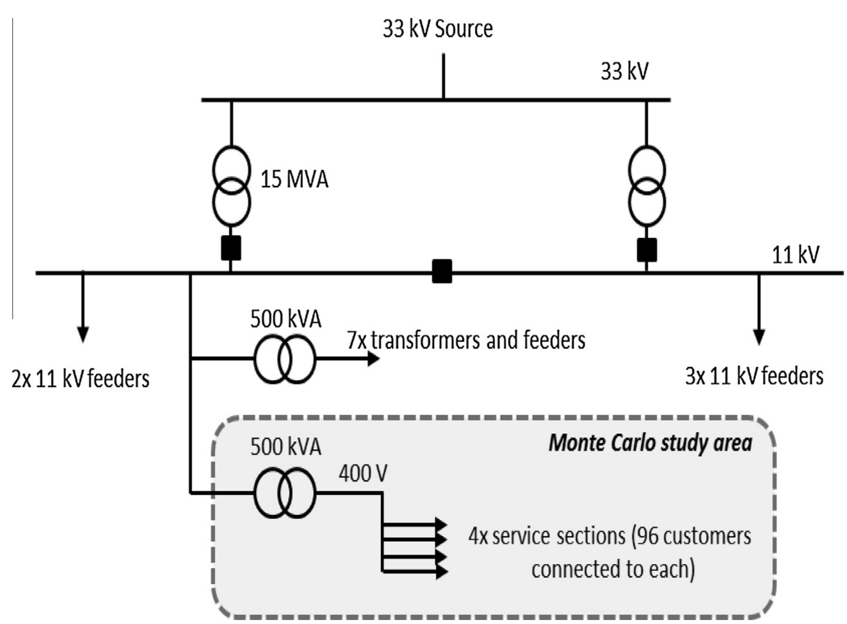

Fig. 8. UK generic network used in steady-state IPSA2 and dynamic PSCAD studies.

EV penetration is defined as the ratio of EVs to the number of vehicle-owning households. For the case of the urban network with 288 customers and a vehicle ownership of 86%; 60% penetration (149 EVs) represents an approximate nominal upper bound on the test networks whereupon all households owning more than one vehicle have an EV as the second vehicle.

1000 simulated peak days (i.e. 1000 simulation runs) were generated to ensure adequate variation of customer behaviour, EV charging profiles and customer location on the network. The generation of multiple random configurations naturally captures any spatial concentration of households with EVs (e.g. at the remote end of the longest feeder) which could cause additional voltage drops. Fig. 10 shows some illustrative examples from the urban profiles population assigned to customers.

A configuration of the urban network with 60% EV penetration at 18.00 on the peak demand day was examined to ensure that stable results had been obtained with 1000 MCS trials. With 1000 trials, the mean transformer demand had converged to a stable 385.8 kVA (standard error 0.29 kVA). The standard deviation of the distribution of transformer demands had also stabilised to

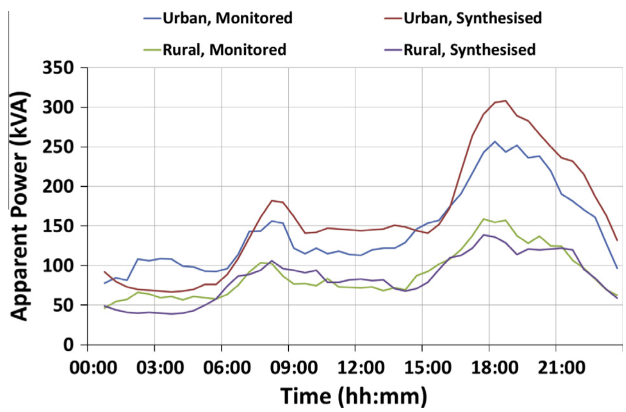

Fig. 9. Comparison of monitored and synthesised load profiles for a rural and urban substation.

9.1 kVA. Thus the distributions produced by the simulated trials are stable and provide reliable estimators of the simulated demand.

(details in Section 4), has also been modelled in PSCAD/EMTDC version 4.2.1. PSCAD/EMTDC is a commercial power systems analysis software package developed by the Manitoba HVDC Research Centre [28] and originally inspired by Dommel [29,30]. It uses time-domain based analysis (as opposed to frequency domain like IPSA2) and was used in this study primarily to evaluate the impact of unbalanced loads on the resultant voltages within the network.

In contrast to the approach of using the average and 97.5% load values in the IPSA2 simulations, each load profile for the 1000 simulated peak days was used in PSCAD and the voltage magnitude and voltage unbalance was assessed once each simulation reached steady-state. This was undertaken for different EV penetration levels ranging from 0% to 100% in 5% steps. To reduce the computational burden in PSCAD, only the worst-case hours of the peak day were assessed. This was 17.00–05.00 based on the IPSA2 results.

The voltage unbalance in a three-phase system is defined in Engineering Recommendation P29 [31] as the ratio (in per cent) between the rms values of the negative sequence component and the positive sequence component of the voltage. This can be approximated for values of voltage unbalance of a few per cent, as was the case for this study, as:

$$\text{Voltage unbalance } (\%) = \frac{\text{Maximum deviation from the average of the three phase voltages}}{\text{Average of the three phase voltages}} \times 100\%$$

3.2. Steady State, balanced study in IPSA2

Each of the three networks; urban, rural and generic were modelled in IPSA2, version 2.3.1. IPSA2 is a commercial power systems analysis software package developed initially by the University of Manchester Institute of Science and Technology (UMIST) in 1975 and is now supported by TNEI Services Ltd [26]. The IPSA2 load flow algorithm, based on the Fast Decoupled Newton–Raphson algorithm [27], was used to calculate the power flows and voltages throughout the system.

The average hourly load profiles (expected values) of the households on the networks with a defined EV penetration were calculated from the 1000 runs. In addition the 2.5% and 97.5% lower and upper bounds of the data were calculated. Fig. 11 illustrates these calculations for the remote end of the longest feeder on the urban network (10 households connected to that feeder) at 60% EV penetration; the expected values are represented by the black dots and 95% of the data falls within the grey area.

Network simulations in IPSA2 were performed using the average and 97.5% upper bound load data for the EV penetration levels of 15%, 30% and 60%, producing corresponding power flow and voltage drop results for the various configurations of the two networks. Two additional EV penetrations –40% and 50%– were studied for the generic network to consider the thermal loading of the transformer in greater detail.

3.3. Electromagnetic transient, unbalanced study in PSCAD

IPSA2 is unable to calculate voltage unbalance caused by phase concentration of existing load and EVs, and therefore the voltage drop along the feeder calculated by IPSA2 would be an underestimate when the network is unbalanced. In order to overcome these limitations, the network demonstrating the worst case results as calculated by IPSA2, the Generic distribution network

4. Results

4.1. Transformer loading

Fig. 12 shows power demand profiles for the urban and rural LV networks on the test day for EV penetration values that produce loading exceeding the transformer thermal limit. Using the 97.5th upper demand bound, the urban network is not compromised even at 60% EV penetration, although at this point the load is approaching the transformer rating (500 kVA). The rural network was compromised at 15% penetration. The generic network was compromised at 40% EV penetration using the 97.5th upper demand bound (Max@ 40%) (Fig. 13).

4.2. Voltage-IPSA2 study

The voltage magnitude in LV networks is required to be within the statutory limits +10%/−6% [32]. Table 2 shows the maximum voltage changes occurring at times of 97.5% of the load for the rural and urban networks. Similarly in Table 3 and 60% EV penetration with 97.5% of the load did not cause voltage problems in the generic LV distribution network.

4.3. Voltage and phase unbalance – PSCAD study

The worst case for voltage drop is at the furthest end of the feeder, and therefore the voltage and its unbalance were measured at the end of the 400 V feeder. Industry planning regulations state that the voltage unbalance should not exceed 2% when assessed over any one minute period, and when sustained the voltage unbalance should not exceed 1.3% for systems with a nominal voltage below 33 kV [31]. The minimum voltage magnitude experienced for each EV penetration level during all the studies is

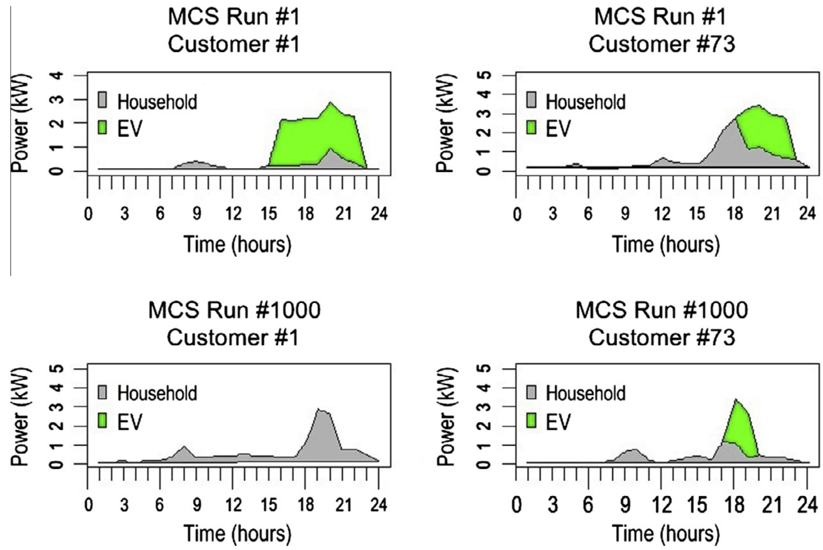

Fig. 10. Example of peak day load profiles for 2 customers (#1 and #73) on the network for 2 different MCS runs (run #1 and 1000). Each MCS run generates a population of customers as defined by the network topology.

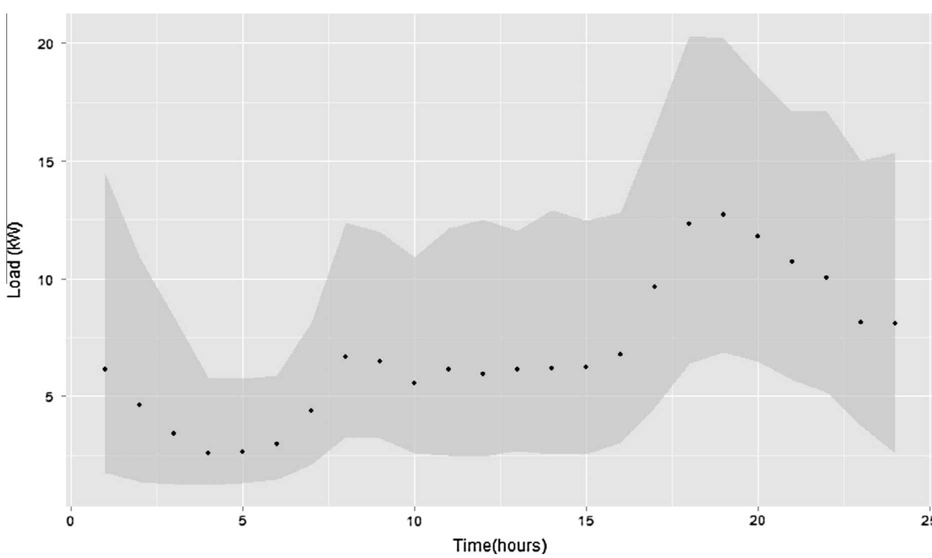

Fig. 11. Remote end of longest feeder-urban 60% EV penetration-average load values (dots) and 95% data bound (grey area).

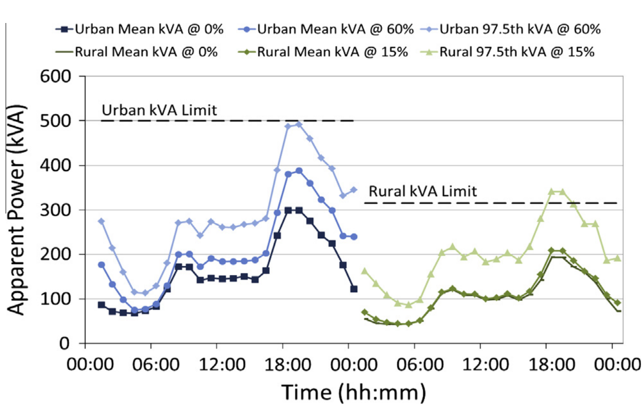

Fig. 12. Test day critical demand for urban and rural network.

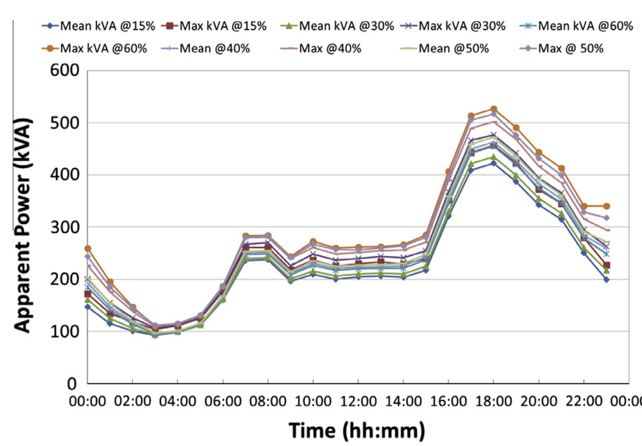

Fig. 13. Test day critical demand for the generic network.

Table 2
Maximum voltage changes on the test networks (negative sign indicates a voltage drop).

	Average Load 0% EVs	Average Load 15% EVs Rural 60% EVs Urban	97.5% Load 15% EVs Rural 60% EVs Urban
ΔV – Rural	−2.33%	−2.52%	−5.39%
ΔV – Urban	−1.40%	−1.72%	−2.90%

Table 3
Maximum voltage changes in the generic LV network (negative sign indicates a voltage drop).

Lowest voltage	15% EVs	30% EVs	60% EVs
ΔV – Mean (%)	−1.58	−1.64	−1.73
ΔV – Max (%)	−2.67	−2.79	−3.02

shown in Fig. 14 and the maximum voltage unbalance during all the studies is shown in Fig. 15. The results for minimum voltage are consistent with the maximum loading condition of the IPSA2 study. The PSCAD results show a marginally lower minimum voltage than IPSA2 results as the unbalance in load and EV connections across the LV network is now modelled. As the penetration of EVs increases the load increases and the minimum voltage experienced reduces, although it does not cause a statutory limit violation even with 100% EV penetration.

Similarly an increase in charging load results in the unbalance of the network increasing. Using the 97.5% percentile, an EV penetration of 60% can be sustained on the generic network before the voltage unbalance would be considered an issue.

CLNR field trials networks, in the authors' experience, have been observed to exhibit a voltage unbalance that frequently approaches or exceeds the 1.3% limit-with no EVs charging at all. Therefore, the impact of high EV penetrations on unbalance should not be ignored. All networks are different and as EV penetrations increase,

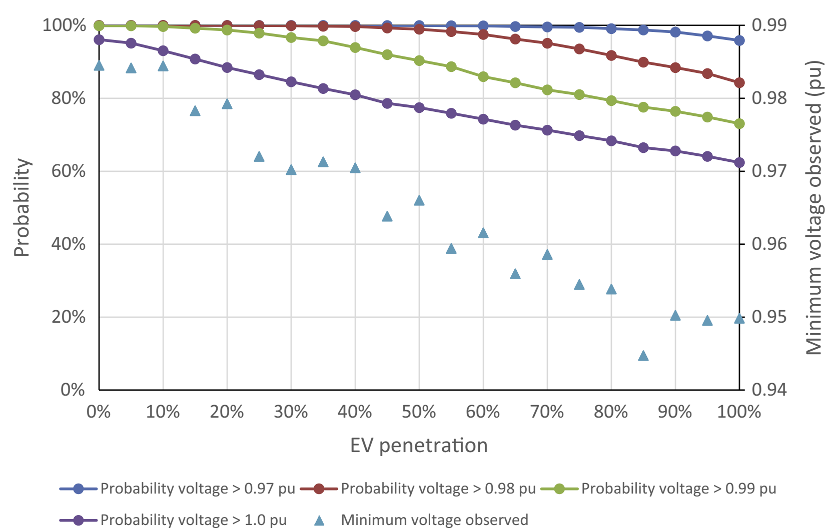

Fig. 14. Minimum voltage magnitude observed for each EV penetration during all studies.

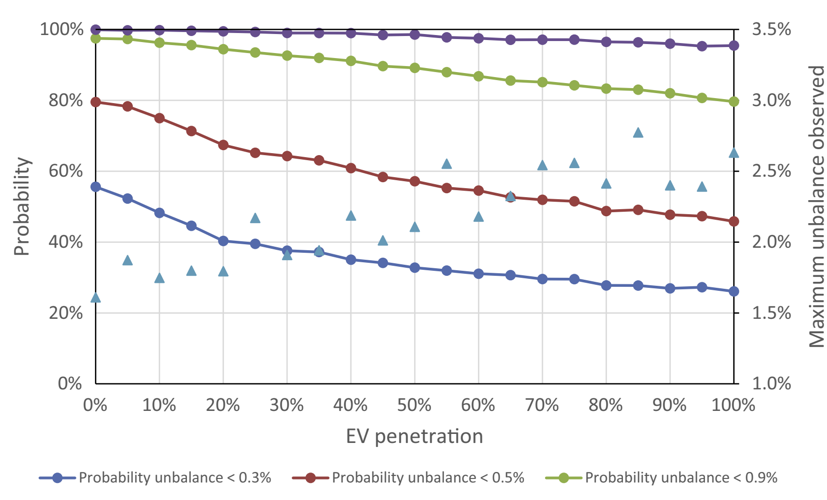

Fig. 15. Maximum voltage unbalance observed for each EV penetration during all the studies.

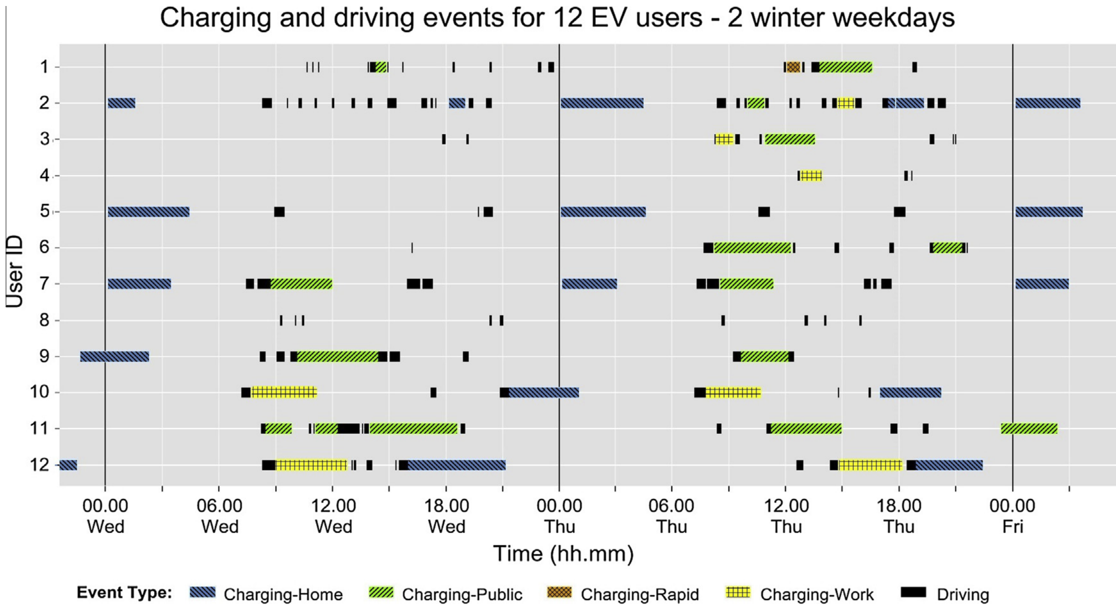

Fig. 16. Spatial and temporal diversity of EV charging demand.

the determination of the degree of unbalance will need to be conducted on a network-by-network basis.

5. Discussion and conclusions

This work has used a probabilistic method to combine two unique datasets of real world EV charging profiles and residential smart meter load demand. The datasets were used to study the impact of the uptake of EVs on distribution networks. The study used real, validated networks of an urban and rural area and a generic network, representative of heavily-loaded UK distribution networks. The range of networks used demonstrated that LV networks are not a homogenous group and have different characteristics, sets of parameters and customer behaviour which illustrates the importance of bespoke studies.

5.1. Urban vs rural study

The urban network under study was able to accommodate a much higher EV penetration compared to the rural network. These results stem from the differences in EV charging profiles, network topologies and impedances between the urban and rural areas. The trial data showed that rural users relied on domestic charging more than the urban users who had access to a more extensive public charging infrastructure. In addition, the SoC data indicates that the median SoC start for urban users is 56.3% compared to 47.9% for rural users indicating more energy used for journeys of rural users-suggesting longer trips back home.

5.2. Urban vs generic study

The generic network gives broad and generalisable findings in comparison to more specific findings respective to a specific network (i.e. real urban network). However, the generic network is a heavily loaded network and simulating it using peak day load data at the 97.5th upper demand bound could be considered conservative. Lower EV penetration rates (40%) caused thermal overloads on the generic network compared to the urban network. Working with the heavily-loaded generic network gives insights to future problems on the networks due to a transition to a low carbon economy (i.e. the use of heat pumps, distributed generation and the likely growth in EV battery capacities and charger power). EV loading at different levels erodes the headroom available at peak loading time which implies that the capacity of the network to absorb additional large electrical load (e.g. heat pumps) is reduced and also impacts on voltage unbalance particularly in areas of high PV penetration.

This comparison between the generic and urban networks shows that while currently few networks are likely limited to accommodate EVs, distribution networks in general are more robust than previous work has suggested. The spatio-temporal spread of charging profiles used in this work-moving away from using a fixed energy, static spatio-temporal charging period contributed to these novel findings.

5.3. Spatial and temporal diversity of EV charging demand

Spatial, temporal and behavioural diversity of EV charging demand has been demonstrated to alleviate the impacts on electricity distribution networks. Based on real world trials of EV usage, the results of this study showed that distribution networks could accommodate higher EV penetrations than previous studies have suggested. The diversity of charging demand in time and space was a consequence of an extensive charging infrastructure available to the EV users which gave them multiple options (work, public, rapid and home) and flexibility of when and where to charge. People charged at more than one location and did not rely only on residential charging. Therefore, additional energy was supplied to EVs from non-domestic sources and people arrived home with a higher SoC on their EV batteries than what would have been assumed. Fig. 16 shows an example of the spatial diversity of charging events in addition to the diversity in charging times, duration and frequency, illustrating the stochastic nature of the expected new electricity demand.

The EU Electricity Directive (2009/72/EC) states that the DNOs are legally responsible for ensuring the long-term ability of the system to meet reasonable demand, for the distribution of electricity [33]. EVs are well suited to meet urban mobility requirements [34] and an uptake of EVs could create a significant new electric demand that the DNOs would need to accommodate [35].

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This study demonstrated the benefits of maintaining load diversity by spreading EV charging demand both in space and time. This suggests that it could be beneficial for DNOs to invest in supporting the roll out of the EV recharging infrastructure and work closely with new market players (e.g. charging infrastructure operators) as a way to efficiently manage existing distribution network infrastructure. In addition to alleviating the impacts on the distribution network and operating a less congested network, an EV charging demand that is spread through space and time could present more opportunities and flexibility for demand-side management schemes. Finally, the real world trial illustrated the stochastic nature of EV charging demand which could create planning uncertainties, for DNOs, associated with any potential plans to upgrade the electricity network.

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